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# Solar-Climatic Relationship and Implications for Hydrology

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Research during the latest years has indicated a significant connection between climate and solar activity. Specifically, a relationship between Northern Hemisphere air temperature and sunspot cycle length (SCL) has been shown. By using monthly SCL and land air temperature from 1753-1990 (238 years) we show that this relationship also holds for a single observation point in south of Sweden. Using data after 1850 yields a statistically significant linear correlation of 0.54 between SCL and mean temperature. Furthermore, we show that there are indications of a low-dimensional chaotic component in both SCL and the interconnected mean land air temperature. This has important implications for hydrology and water resources applications. By pure definition of chaos this means that it is virtually impossible to make long-term predictions of mean temperature. Similarly, because of the strong connection between temperature and many hydrological components, it is probable that also long-term water balance constituents may follow chaotic trajectories. Long-term projections of water resources availability may therefore be impossible. Repeated short-term predictions may, however, still be viable. We exemplify this by showing a technique to predict interpolated mean temperature 6 and 12 months ahead in real time with encouraging results. Improving the technique further may be possible by including information on the SCL attractor. To summarize, research into the possible existence of chaotic components in hydrological processes should be an important task for the next years to come.

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## Introduction

Climatic variables such as insolation and temperature are key elements in hydrological calculations. Due to increased interests during recent years concerning climate variability and its effects on future water resources availability, the scale of interest for hydrologists has started to change from the typical catchment to regional or even global processes (*e.g.* Eagleson 1986). The change in focus of scales is forcing hydrologists to improve the understanding of the climate-atmosphere-land surface as an interactive coupled system.

The possibilities for a significant solar-climatic relationship has been a much debated issue during recent decades (*e.g.* Willett 1974; Muir 1977; Colebrook 1977; Pittock 1978; Reid 1987; Salby and Shea 1991). Many investigations have utilized the sunspot number as an indication of solar activity (Labitzke 1987; Barnston and Livezey 1989; van Loon and Labitzke 1988). However, recent research indicates that the sunspot cycle length (SCL) may be a more important variable to use when studying solar-climatic relationships (Friis-Christensen and Lassen 1991; Kelly and Wigley 1992; Butler 1994). The SCL is defined as the time in years between the cycles of maximum (or minimum) values in the observed sunspot time series (*e.g.* Matsumoto *et al.* 1996*a*; 1996*b*). The SCL has been shown to vary with solar activity so that high activity implies short cycles and low activity long cycles (Friis-Christensen and Lassen 1991). Consequently, the SCL may be said to give a measure of the long-term accumulated energy output of the Sun. Hence, it is reasonable to expect an inverse relationship between SCL and temperature.

If a significant solar-climatic relationship exists it may be utilized to improve the prediction accuracy for future temperature changes and to improve the understanding of how human activities may influence future climate. Similarly, because of the close relationship between temperature and many hydrological variables (*e.g.* evapotranspiration, runoff, *etc.*) this information may be utilized to make future projections of trend in hydrological components.

Several studies during recent years have indicated nonlinear and chaotic properties for sunspots and solar activity in general (Ruzmaikin 1981; Zeldovich and Ruzmaikin 1983; Gilman 1986; Kurths and Herzel 1987; Weiss 1988; Feynman and Gabriel 1990; Mundt *et al.* 1991; Berndtsson *et al.* 1994; Jinno *et al.* 1995). Mundt *et al.* (1991) noted that one reason why models based on periodic behavior fail to predict sunspot time series accurately, may be the nonlinear behavior of the time series. Recently, studies that consider the chaotic properties of the Sun's behavior have indicated that better predictions can be made using developments within chaos theory (Kurths and Herzel 1987; Weiss 1988; Mundt *et al.* 1991).

As mentioned above, it is important to establish causal relationships between climate and other readily observable variables. Friis-Christensen and Lassen (1991) and Kelly and Wigley (1992) both found a link between SCL and land air temperature. There was, however, a significant difference in results depending on different filtering methods. Butler (1994) also found a significant relationship between SCL and land air temperature at a point. All previous authors considered temperature records from the mid-19th century. In this paper we examine the dependence between a longer temperature time series (1753-1990) at a point and the SCL. We make a comparison between a linear and a nonlinear interpretation of the dependence. The results of the analysis are exploited by designing a prediction model for interpolated temperature in real-time. We close with a discussion on the importance of the results for hydrological applications and some important areas for future research.

## Data Base and Methodology

We use monthly temperature time series observed in Lund in the south of Sweden since 1741 (Tidblom 1876). Because of some gaps in the observations during the early years of measurements we analyze monthly series from 1753-1990 (238 years). Uncertainties and errors are inherent in such long and old records. The location for observations has changed three times for the temperature gage. Also the type of gage and the use of wind shield have varied. The largest horizontal distance change for the gage has been about two km. Simultaneous observations over a 6-year period for temperature at these two locations indicated, however, an absolute average difference of only 0.16°C (Andersson 1970). An investigation by Andersson (1970) for the data between 1867-1956 showed that the series may be considered homogeneous.

Another and perhaps a more important type of error is systematic errors caused by gradually changing conditions at the observation site. This type of error may include local warming effects of the gradually growing urban area where the gage was located. Urban developments have previously been shown to have pronounced effects on local temperature records (Balling and Idso 1989). Kawamura *et al.* (1993) showed that a statistically significant linear trend can be identified in the utilized monthly temperature time series. The increasing linear trend corresponds to about 0.84°C per 100 years. It may be assumed that a significant part of this linear trend is related to the urban growth and industrialization of the city of Lund (at present a population of about 80,000 inhabitants).

Monthly sunspot numbers were compiled from Chernosky and Hagan (1958) and consecutive volumes of J. Geophys. Res. Sunspot numbers were cleaned by using the noise reduction algorithm of Schreiber (1993; see also Jinno *et al.* 1995). This algorithm was especially developed for nonlinear estimations. Known methods for nonlinear and chaotic attractor estimations are extremely noise sensitive, and it is therefore necessary to work with cleaned data (Grassberger *et al.* 1991).

There is no unique way of determining SCL values. Lassen and Friis-Christensen (1992) determined SCL values by using epochs of maxima and minima from the secular smoothing procedure introduced by Gleissberg (1944). The procedure corresponds to the application of a low-pass filter with coefficients 1, 2, 2, 2, and 1 to the series of individual sunspot maximum and minimum epochs. We compare their SCL values with raw data and our own estimations from the above nonlinear noise reduction scheme of Schreiber (1993).

To obtain SCL values and corresponding average temperature, epochs between minima and maxima of monthly sunspot values were determined. This basic procedure was used for both raw and noise reduced sunspots. After maxima and minima epochs were determined, the average temperature for those periods was calculated from the 238-year monthly time series.

Lorenz (1963) was the first to display possible chaotic properties of the atmosphere. He showed that a dynamic system may be described by

$$\frac{dx}{dt} = F(x) \tag{1}$$

where $t$ denotes time that is the only dependent variable. The vector $\boldsymbol{x} = (x_1, x_2, x_3, \ldots, x_n)$ represents a state of the system and a set of $n$ ordinary differential equations and can be thought of as points along a time axis in phase space where the vector $\boldsymbol{F}$ is a nonlinear operator acting on $\boldsymbol{x}$. For some initial conditions the vector $\boldsymbol{x}$ can be shown to have a chaotic evolution, *i.e.*, $\boldsymbol{x}$ approaches a strange attractor. At small changes of the initial conditions, $\boldsymbol{x}$ will have a very different evolution. Eq.(1) can be expressed as a single nonlinear differential equation according to

$$x^{(n)} = f(x, x', \ldots, x^{(n-1)}) \tag{2}$$

This in turn is equivalent to

$$x(t) = (x(t), x'(t), \ldots, x^{(n-1)}(t)) \tag{3}$$

In the climatological reality, however, $\boldsymbol{F}(\boldsymbol{x})$ and initial conditions are unknown. Instead, one often has observations of $x(t)$, *e.g.* temperature, precipitation records, *etc.* According to a theorem by Takens (1981) (see also Ruelle 1981; Packard *et al.* 1980) it is possible to use the observations $x(t)$ to evaluate the dimension of the attractor.

The general procedure to evaluate the attractor dimension is to perform a phase space (sometimes called state space) reconstruction. The basic idea behind a phase space reconstruction is that the past and future of the time series contain information about unobserved state variables that may be used to define a state at the present time (Casdagli *et al.* 1991). The procedure of phase space reconstruction is motivated due to unknown properties of the dynamical system such as relevant variables and their total number. Phase space reconstruction was introduced in dynamical systems by Packard *et al.* (1980; see also Ruelle 1981; Takens 1981), even though the basic idea goes as long back as Yule (1927).

For deriving the dimension $d$ of the attractor from observations $x(t)$ it is sufficient to embed it in an $m$-dimensional space ($d<m$, $n$)

$$x(t) = (x(t), x'(t), \ldots, x^{(m-1)}(t)) \tag{4}$$

Consequently, it is not necessary to know the original system's dimension or state variables as long as $m$ is chosen large enough ($m=2d+1$; Takens 1981). According to this and introducing a time lag $\tau$ one gets (Grassberger and Procaccia 1983*a*; 1983*b*)

$$x(t),\ x(t+\tau),\ x(t+2\tau), \ldots,\ x(t+(m-1)\tau) \tag{5}$$

Following Eq. (5), new time series are generated according to

$$\begin{array}{l} x(t_1), x(t_2), \ldots,\ x(t_N) \\ x(t_1+\tau),\ x(t_2+\tau), \ldots,\ x(t_N+\tau) \\ x(t_1+(m-1)\tau),\ x(t_2+(m-1)\tau), \ldots,\ x(t_N+(m-1)\tau) \end{array} \tag{6}$$

where $N$ is a set of points on the attractor embedded in the $m$-dimensional phase-space. In the vector $\boldsymbol{x}$ with the coordinates $[x(t_1), \ldots, x(t_i + (m-1)\tau]$, a point can be chosen $\boldsymbol{x}_i$ so that all distances $|x_i - x_j|$ for $m$-1 points can be calculated. By repeating this for all $i$ one gets

$$C(r) = \frac{1}{N(N-1)} \sum_{i,j=1}^{N} \theta(r - |x_i - x_j|) \tag{7}$$

where $\theta$ is the Heaviside function defined by $\theta(x) = 0$ if $x<0$ and $\theta(x)=1$ if $x>0$. The entity $C(r)$ is called the correlation dimension or correlation integral for the strange attractor and defines the density of points around a specific coordinate $\boldsymbol{x}_i$. A possible approach to estimate the correlation dimension for time series is to use the algorithm according to Grassberger (1990). The correlation integral $C(r)$ is used to describe the dimension $d$ of the attractor, *i.e.*, if the attractor is a line, surface or volume. If the attractor can be described by a line one expects that the number of points within a distance $r$ from a coordinate is proportional to $r/\varepsilon$, where $\varepsilon$ is a point in the middle of the attractor. If, on the other hand, the attractor is a surface $C(r)$ is proportional to $(r/\varepsilon)^2$, and similarly if the attractor is a volume $C(r)$ should be proportional to $(r/\varepsilon)^3$. Consequently, we find that for small $r$, $C(r)$ should relate as

$$C(r) \sim r^d \qquad i \neq j \tag{8}$$

Values of $d$ that are not integers indicate a fractal and thus chaotic attractor. The dimension $d$ of the attractor is given by the slope of log $C(r)$ for the slope of log $r$ according to

$$\log C(r) = d|\log r| \tag{9}$$

The phase-space characteristics of the attractor indicate the temporal properties of the system and how well prediction may be performed. The dimension of the attractor, according to above, signifies how many variables that are necessary to describe the evolution in time. For example, $d = 2.5$, indicates that the time series can be described by an equation system containing three mutually independent variables. It is, however, difficult to estimate the structure of the equation system. This is subject to intensive research (*e.g.* Rössler 1976; Gousbet 1991*a*; 1991*b*; Xu *et al.* 1993; Kawamura *et al.* 1996*a*; 1996*b*).

The use of Eq. (7) has, however, been criticized because its sensitivity to noise, boundary effects, and length of the time series (*e.g.* Theiler 1986; 1991; Grassberger *et al.* 1993). Therefore, several independent methods to determine the dimension have to be used. A test that allows one to estimate an integer dimension $d_E$ that is the minimum needed to unfold the dynamics of the attractor has been delineated by Kennel *et al.* (1992; see also Abarbanel 1996). The method is described as the global false nearest neighbors (Abarbanel *et al.* 1993). The method involves the examination, in dimension $d$, the nearest neighbor of every vector $\boldsymbol{x}$ in dimension $d+1$. If the nearest neighbor shifts away from $\boldsymbol{x}$ when the dimension is increased, then it is designated a false neighbor as it moves far away from the attractor. Consequently, when the percentage of false neighbors approaches zero the structure of the attractor has been unfolded (Abarbanel and Lall 1996).

The phase-space characteristics of the attractor indicate the temporal properties of the system and how well prediction may be performed for future times. A quantitative estimate of the system's predictability is the Lyapunov exponent. It measures the system's speed of divergence of trajectories from nearby initial conditions (Abarbanel 1996; Rodriguez-Iturbe *et al.* 1989). Given a continuous system in the $n$-dimensional phase space, long-term changes are monitored in an infinitesimal $n$-sphere. This sphere will develop into an $n$-ellipsoid due to the locally deforming flow. The $i$th one-dimensional Lyapunov exponent can be defined regarding the length of the ellipsoidal principal axis $p_i(t)$ according to (Rodriguez-Iturbe *et al.* 1989).

$$\lambda_i = \lim_{t \to \infty} \frac{1}{t} \log_2 \frac{p_i(t)}{p_i(0)} \tag{10}$$

where $\lambda_i$ is from largest to smallest. The Lyapunov exponent is consequently related to the expansion or contraction of different directions in the phase space. An algorithm to estimate Lyapunov exponents from time series was given by Wolf *et al.* (1985). The first Lyapunov exponent is estimated as

$$\lambda = \frac{1}{t_N - t_0} \sum_{k=1}^{N} \log \frac{s(t_k)}{s_0(t_{k-1})} \tag{11}$$

where $s_0$ is a measure of the initial distance between two nearby starting points. For a small time later the distance will be $s(t) = s_0 2^{\lambda_1 t}$. Here, the largest Lyapunov exponent, $\lambda_1$, governs the linear ellipsoid growth by $2^{\lambda_1 t}$. According to Moon (1987), $\lambda>0$ indicates chaotic motions.

In this paper, we use the approach of Brown *et al.* (1991) implemented in the software cspW (Randle Inc. 1996) to estimate Lyapunov exponents. This is done by estimating the local Jacobian matrices for underlying dynamics $y(n)$.

A possible prediction approach is to interpret the attractor dynamics in form of local maps (Abarbanel 1996). Using the points $y(k)$ with their neighbors $y^{(u)}(l)$; $u=1,2, ..., N_B$, local functions can be built that continuously extend into the next neighborhood: $y^{(u)}(l) \rightarrow y^{(u)}(u; l+1)$. The local map $G_l(y^{(u)}(l))$ that fits this purpose is determined by the least squares fit (Abarbanel 1996)

$$\sum_{u=1}^{N_B} |y(u;l+1) - G_l(y^{(u)}(l))|^2 \tag{12}$$

Local polynomials are trained on the local maps and forward prediction from a point $z_0$ is based on these maps. The nearest neighbor $w(Q)$ is found for the new point $z_0$. The predicted point $z_1$ is calculated as (Abarbanel 1996)

$$z_1 = G_Q(z_0) \tag{13}$$

It should be mentioned that both global and local approximations exist for the above calculation procedure (see *e.g.* Porporato and Ridolfi 1997; Farmer and Sidorowich 1987; Crutchfield and McNamara 1987; Linsay 1991). In this paper, we will use local approximations however.

The question whether time-varying climatological phenomena have low-dimensional properties or not is a much discussed issue at present. In fact, the complexity of climatological systems and the large number of degrees of freedom make it unlikely that, *e.g.* precipitation is purely governed by a system of few variables (*e.g.* Lorenz 1991). However, if elements of observed time series can be shown to obey deterministic chaos, *e.g.* underlying trends, then a more complete understanding of the system and possibly better prediction techniques can be achieved.

## Linear Relationship Between SCL and Temperature

Fig. 1 shows a comparison between different ways to determine SCL values. The figure shows raw data, smoothed values from Lassen and Friis-Christensen (1992) (below denoted LFC 1992), and smoothed sunspot values from the nonlinear noise-reduction procedure by Schreiber (1993). By using the data from 1753-1990, totally 42 points were obtained for the relationship between temperature and SCL. The main impression from the figure is that the SCL from raw data and the nonlinear smoothing agrees rather well while that of LFC (1992) diverges from the other two

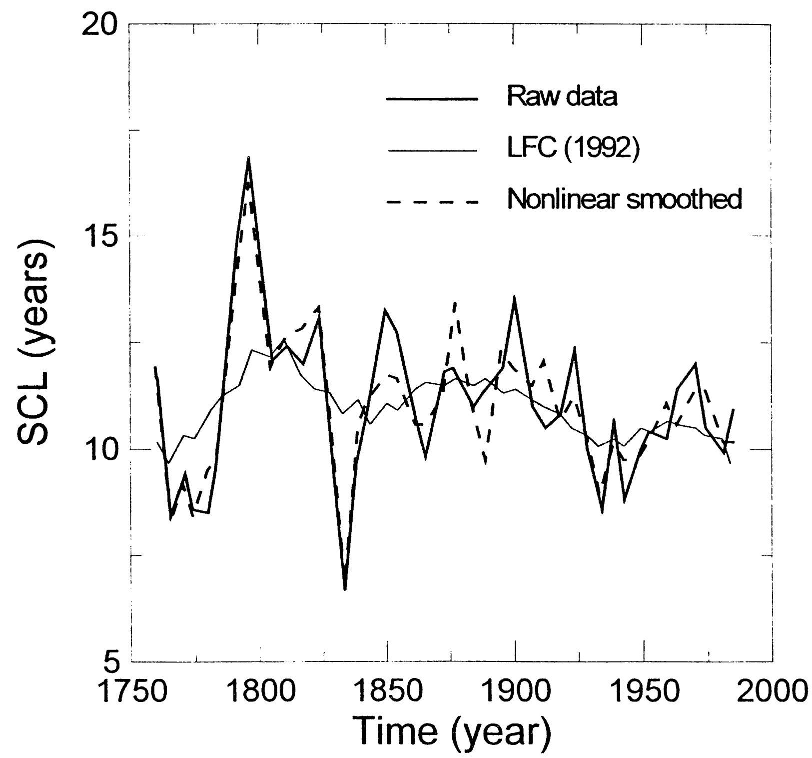



Fig. 1. Comparison between SCL values from raw data, from Lassen and Friis-Christensen (LFC; 1992), and from the nonlinear smoothing procedure of Schreiber (1993).

especially for the extreme maximum and minimum at around 1800 and 1830, respectively. The general appearance of the SCL from raw data and from the nonlinear smoothing agrees better to the SCL derived by Kelly and Wigley (1992) especially for the period before 1850. The peaks and bottoms for the SCL time series derived in this paper are, however, much more pronounced because no filter was applied to the SCL series itself as in Kelly and Wigley (1992) and in LFC (1992). Instead the nonlinear filter was applied to the original sunspot time series before deriving SCL values.

Table 1 summarizes the linear relationships between SCL and mean temperature obtained by using raw and treated data. As seen from the table the highest linear cor-

Table 1 – Pearson product-moment correlation coefficients between SCL and temperature (*, **, and *** indicate 0.05, 0.01, and 0.001 significance level, respectively, at which the hypothesis of a correlation coefficient equal to zero can be rejected; $N = 42$).

| Temperature data | SCL<br>Raw data | LFC [1992] | Nonlinear smoothing |
|---|---|---|---|
| Raw monthly | -0.320* | -0.564*** | -0.287 |
| Linear trend removed | -0.436** | -0.418** | -0.354* |

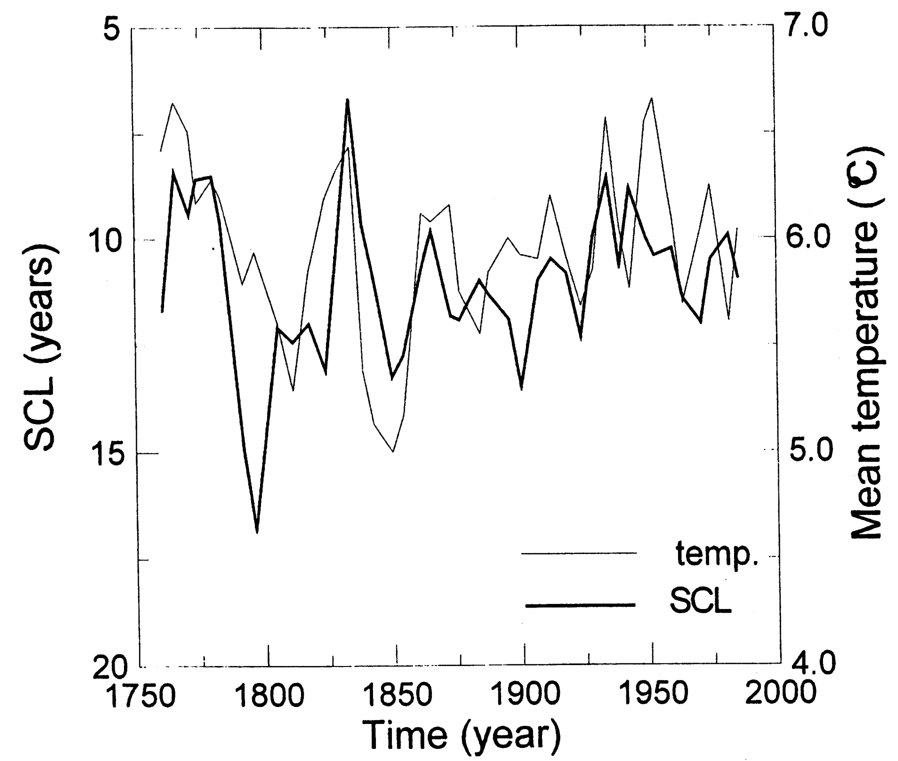



Fig. 2. Raw SCL and corresponding mean temperature for the period 1850-1990.

'elation is obtained using smoothed SCL data from LFC (1992). However, also ısing raw SCL data yields significant correlations of up to -0.436 when the linear emperature trend is removed. The nonlinear smoothing yields a statistically signifi-:ant relationship only when the linear temperature trend is removed.

It is worth noting that when dividing the data into two periods, before 1850 and ıfter 1850, the correlation using raw SCL data changes to –0.395 and –0.544 (see Fig. 2), respectively. Consequently, when using more recent data the correlation in-:reases significantly. A possible explanation for this is that the data after about 1850 ıre more reliable. For temperature this is undoubtedly the case because gage types ınd shelters were standardized in Sweden from about the mid-19th century (Anders-son 1970).

## Nonlinear Relationship Between SCL and Temperature

As mentioned above several studies during the latest years have indicated that the behavior of the Sun may be nonlinear and chaotic (Ruzmaikin 1981; Zeldovich and Ruzmaikin 1983; Gilman 1986; Kurths and Herzel 1987; Weiss 1988; Feynman and Gabriel 1990; Mundt *et al.* 1991; Berndtsson *et al.* 1994; Jinno *et al.* 1995). We, therefore, speculate that also the relationship between the Sun and the Earth's tem-perature, as influenced by a complicated atmospheric flow pattern, may be nonlinear

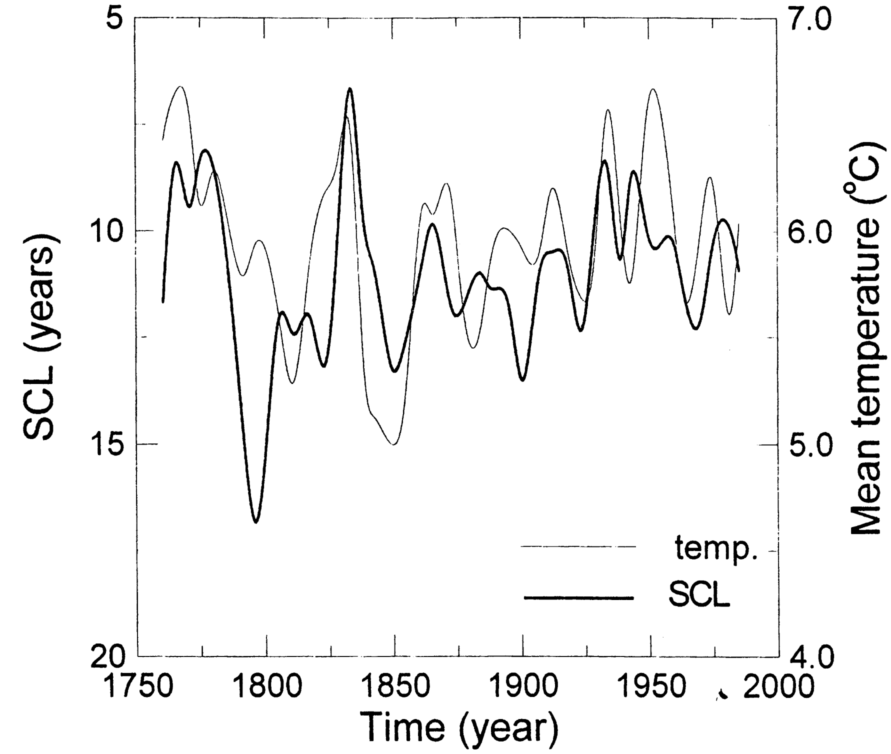



Fig. 3. Raw SCL and corresponding mean temperature interpolated to monthly values by spline functions (data between 1753-1990).

and not easily captured in a simple linear correlation as attempted above (*e.g.* Robock 1978). However, since only 42 observation points are available (Fig. 1) it is difficult to perform a nonlinear analysis. To still attempt this, we interpolated the 42 points for the raw SCL data of Fig. 1 and temperature data by use of spline functions to arrive at monthly values. Fig. 3 shows the outcome of this.

Using the interpolated data for SCL and mean temperature as in Fig. 3, phase space reconstructions were drawn as shown in Figs. 4 and 5. This simply means that the time series is plotted against itself with a proper time lag. This is often done in nonlinear analyses to reveal any structure in future time behavior and properties of the attractor (*e.g.* Henderson and Wells 1988; Tsonis and Elsner 1990). As seen from the figures it appears as if rather clear attractors emerge and that there is a nonlinear behavior of both SCL and temperature. The occurrence of attractors means that the future time behavior is not random but instead appears to settle on a pattern close to that of the attractor. This in turn, may indicate the type and degree of nonlinearity and if it is possible to make predictions into the future for the time series. Of course, interpolated data like this have to be interpreted cautiously and may only indicate properties of the actual process. Even so, it is believed that the phase-space portraits in Figs. 4 and 5 embrace some of the general and longterm behavior of SCL and temperature.

Fig. 6 the resulting $d\log C(r)/d\log r$ vs. $\log r$ according to Eq. (9) for the SCL and

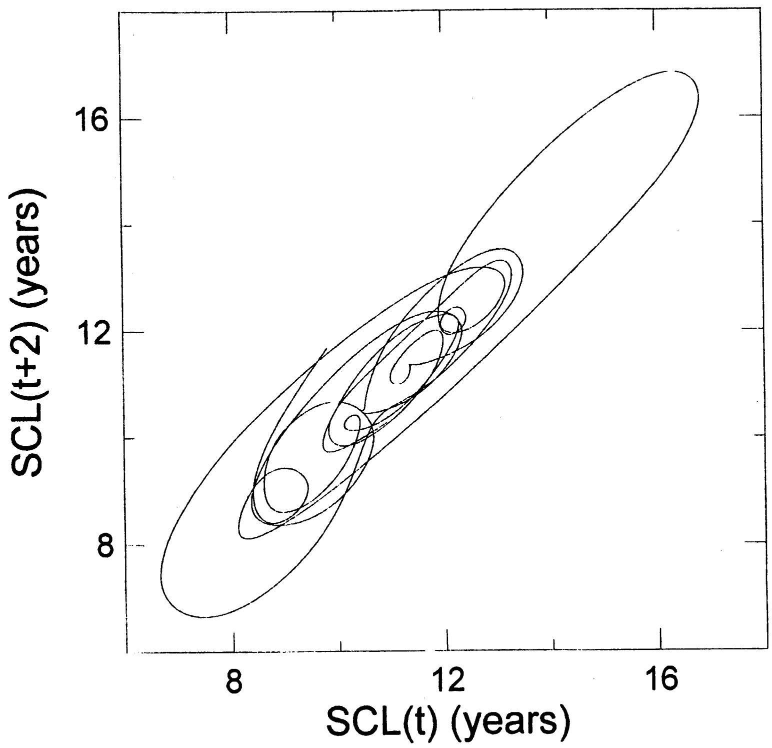



Fig. 4. Attractor for interpolated SCL (data as in Fig. 3). Time lag is 2 years.

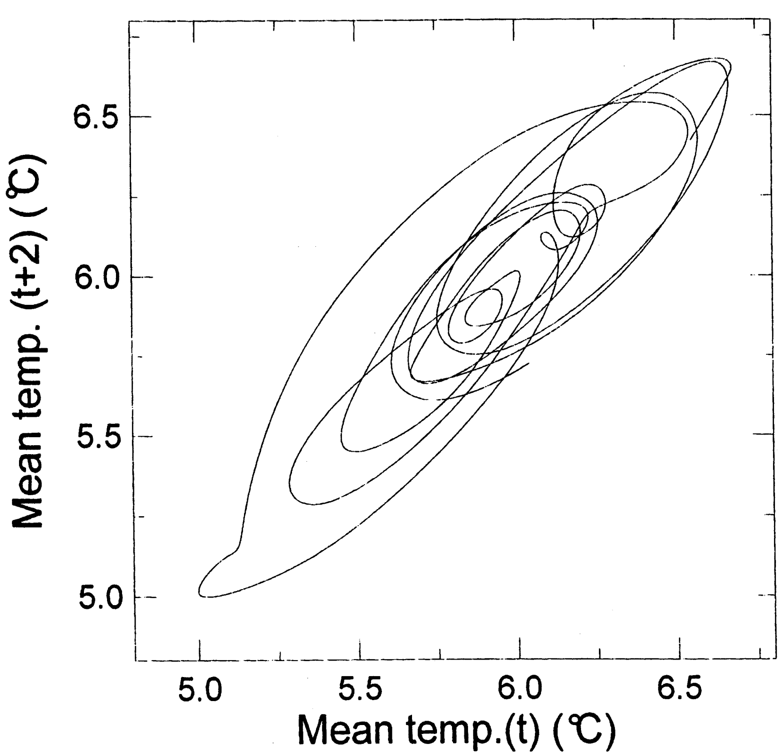



Fig. 5. Attractor for interpolated mean temperature (data as in Fig. 3). Time lag is 2 years.

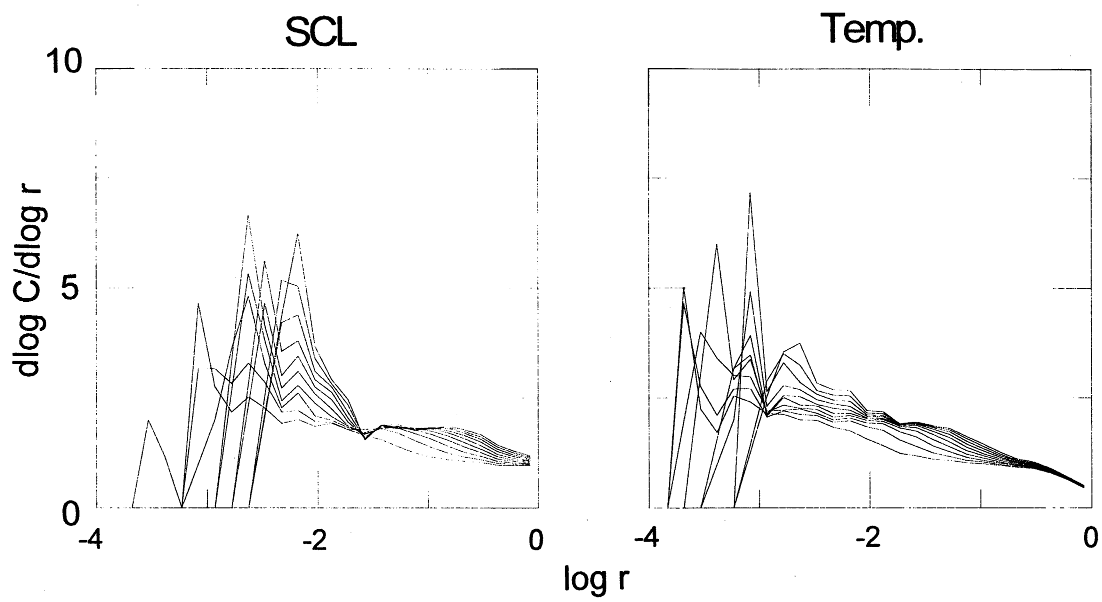



Fig. 6. Slopes *d*log *C(r)*/*d*log *r versus* log *r* for interpolated SCL and mean temperature (data as in Fig. 3).

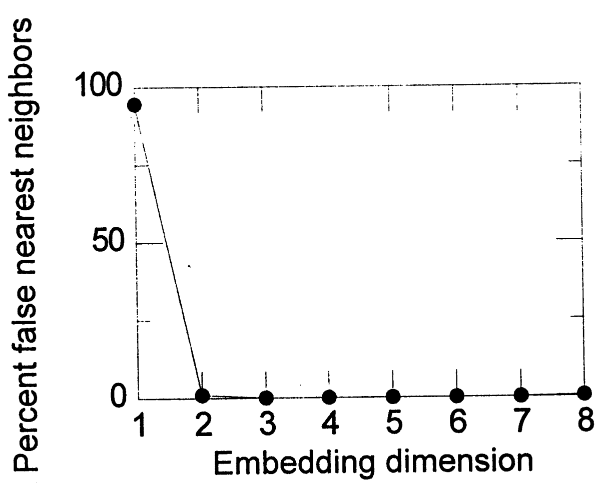



Fig. 7.
Global false nearest neighbors for mean temperature (data as in Fig. 3).

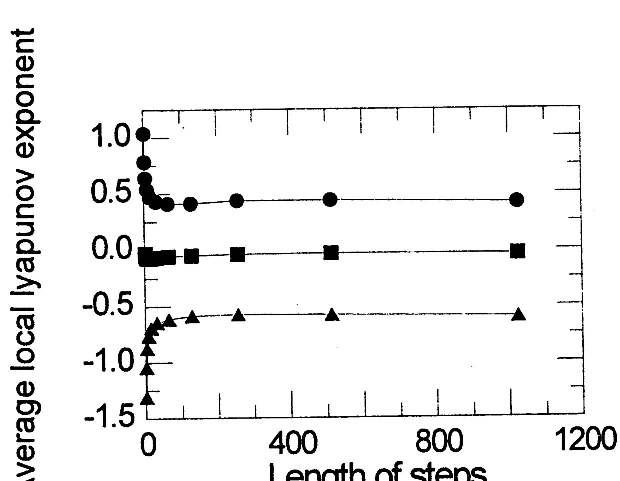



Fig. 8.
Average local Lyapunov exponents for mean temperature (data as in Fig. 3).

:mperature attractors of Figs. 4 and 5. The *m*-embedding was chosen between as $\leq m \leq 10$. Different $\tau$ values were tested but the results proved insensitive to these ariations. As seen from the figures, there is a clear scaling region for $-1.5<\log r<0$ or both SCL and temperature. According to the figure, both SCL and mean temperture display saturation at a correlation dimension $d<2.5$ in this range. Consequenty, a nonlinear equation system with three independent variables would be enough to escribe the evolution in time for SCL and mean temperature (Takens 1981; Ruelle 981).

As mentioned above, however, the algorithm according to Grassberger (1990; Eq. 7)) may underestimate the dimension of the attractor. Therefore, we also used the lobal false nearest neighbor criteria according to Abarbanel *et al.* (1993) using the ommercial software cspW (Randle Inc. 1996). Fig. 7 shows the outcome of this for nean temperature. The figure shows that $d_E$ is selected as 2. Thus, the results conirm the correlation integral estimation.

To further investigate the predictability of interpolated mean temperature, Lyaunov exponents were calculated using the cspW software. Fig. 8 shows the outome of this and the three first average local Lyapunov exponents. From the figure it s seen that the average local exponents converge to approximate global values as $\lambda_1$ = 0.35, $\lambda_2$ = 0.0, $\lambda_3$ = -0.65. If one of the exponents is zero this means that the sytem was properly generated by differential equations. Further, if one exponent is ositive, this indicates a chaotic behavior. As seen from Fig. 8 this is clearly the ase. Also, the Lyapunov dimension can be used to estimate the fractal dimension of he attractor (*e.g.* Abarbanel and Lall 1996). For mean temperature we find this vale to be 2.65 which again confirms that the time series behave according to low-dinensional chaos.

In Fig. 9 we used the information about the local behavior of the attractor and perormed real-time predictions using the methodology according to above. The infornation from the largest Lyapunov exponent ($\lambda_1$ = 0.35) tells us that after about 2 imes 1/0.35 = 2.8, which gives around 6 months, the forecasting ability will quicky be reduced due to the growth of errors. Using the cspW, a local polynomial mod-l (second-order) trained on approximately half of the data (1753-1860). After this, redictions were made in real-time from about 1860 to 1930. As seen from the figre predictions are well in phase with the major peaks and depressions. Several tests or 6-month ahead predictions were made and increasing the lead time. For 6-month redictions results were generally good. However, increasing the lead time quickly lecreased the prediction accuracy. This is in agreement with the largest Lyapunov xponent. An example of 12-month predictions is shown in Fig. 10. It should be nentioned that the model is not updated during the course of predictions in time. Intead, the same model is used as was found best for the calibration period during 753-1860. Fig. 11, finally, shows a comparison with an ARIMA model. This mod-l, however, was updated every 50 months. Even so, as is seen from the figure it loes not give better results than the chaotic model.

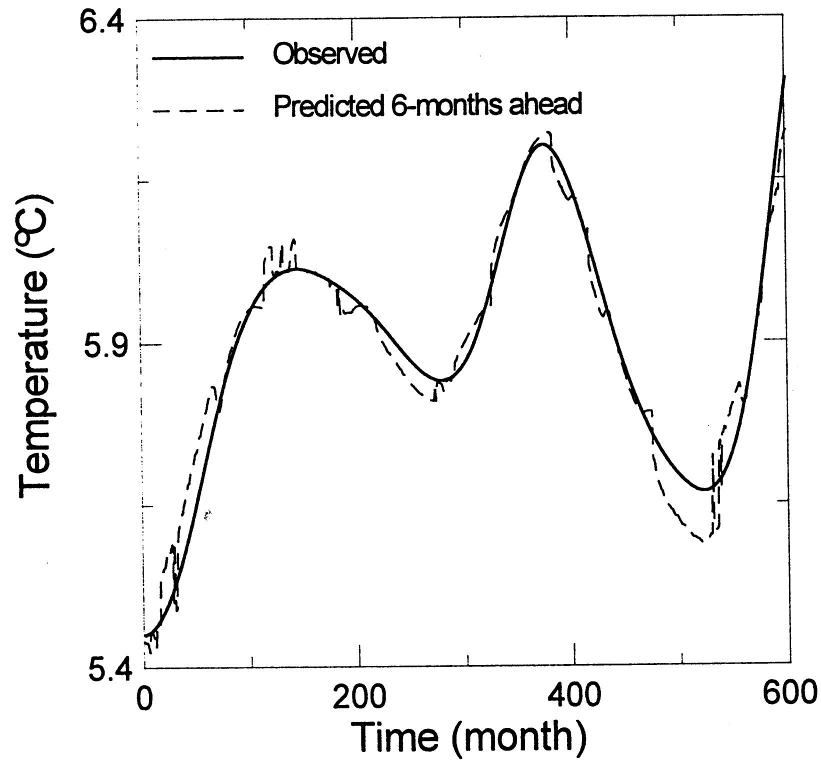



Fig. 9. Real time 6-month predictions of mean temperature using a local linear predictor (data between 1860-1930).

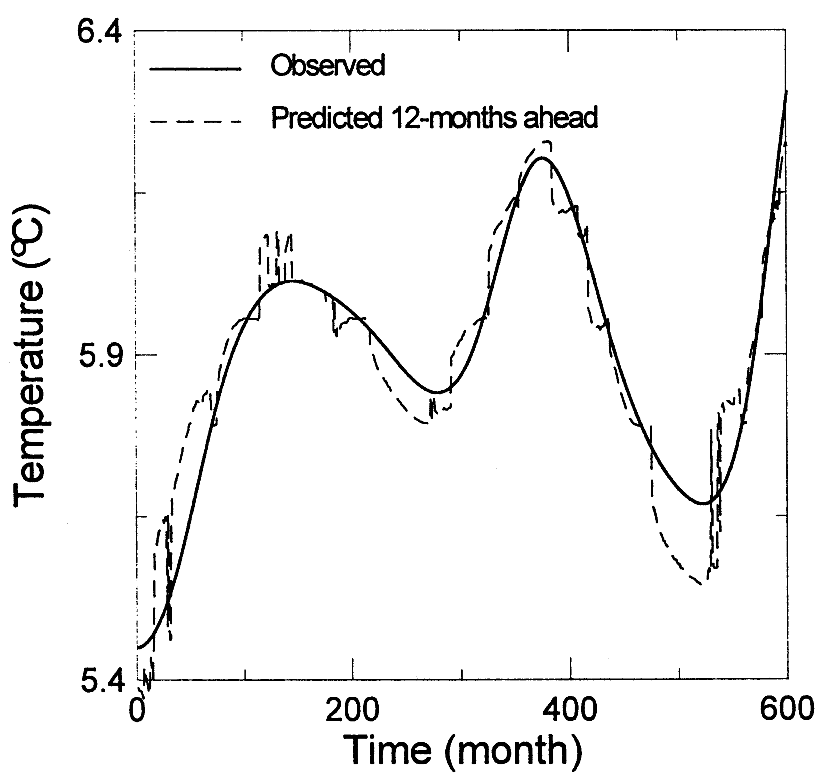
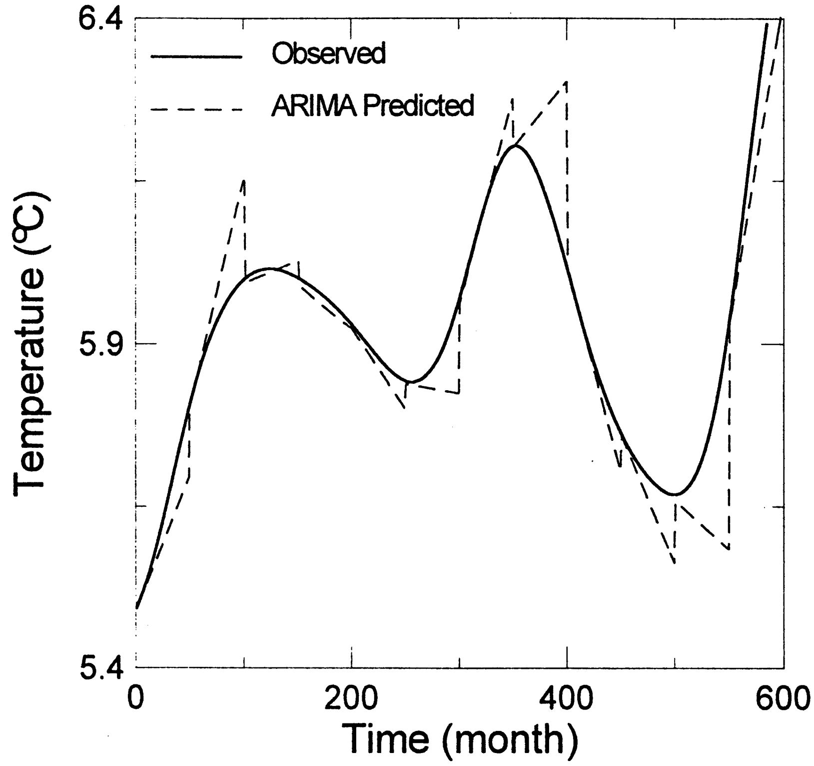



Fig. 10. Real time 12-month predictions of mean temperature using a local linear predictor (data between 1860-1930).




'ig. 11. Real time 6-month predictions of mean temperature using an ARIMA model (data between 1860-1930).

## ummary and Discussion

he results for this study can be summarized as:

) Previous research has shown that there exists a relationship between northern hemisphere mean air temperature and SCL from the mid-19th century (Friis-Christensen and Lassen 1991; Kelly and Wigley 1992). Butler (1994) showed that this is the case also for land air temperature at a point. We confirmed these results and also showed that the statistically significant relationship appears to extend back to the mid-18th century for land air temperature at a point. The relationship was, however, less significant before the mid-19th century, probably because of the poorer quality of temperature data used.

) This study showed that there are indications of a low-dimensional chaotic component in both SCL and the interconnected mean land air temperature. Parts of the variation and sudden jumps in mean temperature can thus be explained by the changes in SCL. The relationship between SCL and mean temperature appears, however, to be a highly nonlinear and complex function.

3) Even if long-term predictions are excluded by the chaotic definition, the short-term time behavior of individual SCL and mean temperature series appears, possible to predict using information about the attractor. We showed that repeated short-term forecasts of 6 months appear to work well.

4) A chaotic behavior in long-term temperature characteristics indicates that hydrological processes coupled to mean temperature may also behave in a chaotic way. Some contemporary research indicates that this is the case for large water bodies (*e.g.* Abarbanel and Lall 1996). Consequently, this excludes long-term predictions into the future. However, even so, repeated short-term forecasts may prove feasible and this may lead forward to a greater understanding of the system's low-frequency behavior and a more broad knowledge and distinction between natural and man-made fluctuations.

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